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Economic Modeling of Income, Different Types of Capital and Natural Disasters

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Abstract

This paper provides empirical estimates of the impacts of natural disasters on different forms of capital (with a focus on human and intangible capital and natural capital), and on real gross domestic product per capita. The types of disaster considered are droughts, earthquakes, floods, and storms and their impacts are measured in terms of the number of people affected or people affected per capita. The authors find statistically significant reductions on the values of human and intangible capital and land capital as a consequence of the disasters, and these reductions are greater when the impacts last for longer periods. Based on the assumption that natural disasters indirectly affect the level of income via losses in capital, the authors estimate a Cobb-Douglas production function using the different forms of capital as inputs. The losses in income are found to vary across different countries and the type of natural disaster studied. However, a common finding is that the losses in income depend generally on two factors: the relative magnitude of impacts of a natural disaster and the values of different forms of capital. The estimates in this paper are national level figures and cannot be useful in predicting the cost of damages at the local level, where much larger amounts can be experienced per capita. Nevertheless, the estimates provide some indication of magnitudes for different disasters and for different groups of countries. More work and more data are needed to get a dynamic profile for the losses of capital and income. But given the study's results, the time profile is estimated to range typically between two and five years.

This paper—a product of the Global Facility for Disaster Reduction and Recovery Unit, ustainable Development Network Vice Presidency—is part of a larger effort in the department to to disseminate the emerging findings of the forth coming joint World Bank-UN Assessment of the Economics of Disaster Risk Reduction. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The team leader—Apruva Sanghi—can be contacted at asanghi@worldbank.org, and the author of this paper at anil.markandya@bc3research.org. We thank Apurva Sanghi and participants at the World Bank for useful comments.

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I. Introduction

Recent work at the World Bank and elsewhere has emphasized the importance of different types of capital in determining a country's productive potential (World Bank, 2006). In particular it distinguishes physical (produced) capital from human, natural and social capital. Each is an important component of wealth and over time, as development takes place, the relative roles of different types of capital change (natural capital as a share of the total declines for example).

One of the issues that arises in understanding the impacts of disasters is how these different types of capital are affected, how they recover after the disaster and how each of them has an impact on output at the national and regional levels.

We postulate that the impact of natural disasters on output is indirect, that is, the natural disasters affect output through their impacts on the different forms of capital (inputs) that make up output. In this regard, the aim of this study is to see how disasters affect the measures of each type of capital and how these changes in capital then impact on output. As expected these impacts will have some dynamic profile and we seek to understand this as much as possible.

II. Four types of capital and data description

In Markandya and Pedroso-Galinato (2007), the production function at the national level was based on four types of capital:

a. Produced or physical capital (PK) – an aggregate of the value of equipments, machinery, structures (including infrastructure) and urban land;
b. Human capital (H) – there are two alternative measures: human capital related to educational attainment (HS), and human capital as part of the intangible capital residual (HR). The *intangible capital residual* consists of human capital and the quality of formal and informal institutions. It is measured as the difference between total wealth and the produced and natural capital (World Bank, 2006).
c. Production and net imports of non-renewable energy resources (E) – sum of the values of oil, natural gas, hard coal and lignite.
d. Land resources (L) – aggregated value of cropland, pastureland and protected areas.

Markandya and Pedroso-Galinato (2007) dealt with cross-sectional data of 208 countries for 2000. The underlying production function was assumed to take a nested CES form. The results indicated a relatively high elasticity of substitutability between different types of capital; for example, loss of natural capital could be made up relatively easily by increases in human and physical capital. In addition, the paper also showed that the efficiency of all capital is significantly influenced by changes in economic indicators (trade openness and private sector investment).

For this study, data on the four types of capital are obtained for three periods – 1995, 2000 and 2005 and for 210 countries, from an updated database underpinning the wealth estimates of nations (World Bank, 2006; G. Ruta and K. Hamilton, personal communication, 2009). The data are measured in per capita values at 2005 constant prices. An econometric analysis is conducted for a panel data of capital, along with the data on the magnitude of natural disasters for the same periods. Because of limitations in the data on human capital related to education (HS), the intangible capital residual (HR) is used as a proxy measure of human capital in this study. Henceforth, HR would be referred in this paper as human and intangible capital. The different types of capital are determined by a number of factors, such as household income, community infrastructures and strength of institutions (see Appendix 1). In addition, we include the magnitude of natural disasters as a determinant in order to examine its impacts on capital. The number of occurrences of natural disasters and the extent of damages are described below.

III. Natural disasters

Four types of natural disasters are considered in the study: droughts, earthquakes, floods, and hurricanes/storms. Data on the number of natural disasters are obtained for 196 countries from the Emergency Events Database (EM-DAT)[1]. *Drought* is characterized by a shortage in a region's water supply as a result of constantly below average precipitation. *Earthquake* is characterized by the shaking and displacement of ground due to seismic waves. This variable refers to the occurrences of earthquakes only without secondary effects. *Flood* is defined by a significant rise of water level in a stream, lake, reservoir or coastal region. *Storm* is represented by wind with a speed between 48 and 55 knots.

Table 1 shows a maximum of 196 countries for which data are available, with a total of 55 events of drought, 82 events of earthquake, 447 events of flood and 303 events of storm that started during the three given periods. A natural disaster, such as drought, may last for several years but the data presented here refer explicitly on the tally of events in a single year, i.e., the year that a natural disaster started. Table 2 presents the countries with more than 3 reported events of a natural disaster in a given year. The highest number of drought events is recorded in China in 2000 (3 incidences). Over the given time periods, China was hit with the most incidences of natural disasters: a total of 5 drought events[2], 8 earthquakes, 23 events of flood and 30 events of storm.

Table 1: Summary statistics of events of natural disasters, by type, 1995-2005.

Natural disaster	Year	No. of observations	No. of events: Total	Minimum	Maximum	Standard deviation
Drought	1995	196	6	0	1	0.17
	2000	196	27	0	3	0.40
	2005	196	22	0	2	0.33
Earthquake	1995	196	26	0	3	0.52
	2000	196	31	0	5	0.62
	2005	196	25	0	4	0.51
Flood	1995	196	95	0	6	1.05
	2000	196	158	0	9	1.54
	2005	196	194	0	17	1.95
Storm	1995	196	76	0	10	1.19
	2000	196	101	0	12	1.50
	2005	196	126	0	14	1.51

[1] http://www.emdat.be/

[2] China had three events of drought in 1995 and two events in 2005.

Table 2: Countries with more than 2 events of a natural disaster per year, 1995, 2000, 2005

Natural disaster	1995	2000	2005
Drought	None	China – 3	None
Earthquake	China, Colombia, Indonesia, Mexico – 3 each	China, Indonesia – 5 each	Turkey – 3 Iran – 4
Flood	Azerbaijan, Brazil, China, India, Iran, Morocco, Pakistan – 3 each Bangladesh – 4 Indonesia, Philippines, United States – 5	Bangladesh, Colombia, Iran, Mexico, Philippines, Solomon Islands, Somalia, Thailand, United Kingdom – 3 each Algeria, Angola, Argentina, Brazil, Indonesia, Italy – 4 each Russia, United States – 5 each China – 9	Bangladesh, Colombia, Haiti, Indonesia, Kenya, Mexico – 3 each Ethiopia, Iran, Venezuela – 4 each Bulgaria, Pakistan, Russia, Vietnam – 5 each United States – 6 Romania – 8 Afghanistan – 9 China – 11 India – 17
Storm	Russia – 3 Australia, Bangladesh – 4 each Mexico – 5 China – 6 Philippines – 7 United States – 10	Australia, Japan, Ukraine – 3 each Mozambique – 4 Philippines – 6 Bangladesh, Vietnam – 7 each China – 10 United States – 12	Jamaica, Japan, Korea Republic – 3 each Honduras, India, Taiwan, Vietnam – 4 each Haiti – 5 Bangladesh – 7 United States – 8 China – 14

One of the approaches in determining the impacts of natural disasters is by looking at the magnitude of impacts in terms of the number of casualties, injuries, people affected and people left homeless as a result of a particular disaster. The relative magnitude of impacts is calculated with respect to a country's total population in a particular year. Table 3 shows the magnitude of impacts *per 1,000 people*. In 1995, the drought events in Zambia affected about 138 for every 1,000 people; while in 2000 and 2005, droughts affected 486 per 1,000 people in Tajikistan and 386 per 1,000 people in Malawi, respectively. Earthquakes caused the largest impacts per thousand of population in Cyprus (2.63), China (1.44) and Chile (1.69) during 1995, 2000 and 2005, respectively. Over the same periods and across the entire sample of countries, floods affected the most number of people in Azerbaijan (196 per 1,000 people), Cambodia (270 per 1,000 people) and Guyana (372 per 1,000 people). Finally the biggest impacts of storm events in terms of people affected occurred in Antigua and Barbuda (956 per 1,000 people) in 1995, Moldova (627 per 1,000 people) in 2000 and Albania (127 per 1,000 people) in 2005. The most number of injuries during the three periods was caused by storm events in 1995, with a total of 3 for every 1,000 people.

Table 3: Number of deaths, injured, homeless and affected people caused by natural disasters per 1,000 people, 1995-2005.

Disaster type	Type of Impact	1995				2000				2005			
		All Countries (n=196)		Country with highest reported impact		All Countries (n=196)		Country with highest reported impact		All Countries (n=196)		Country with highest reported impact	
		Total No.	Stdev	No.	Country	Total No.	Stdev	No.	Country	Total No.	Stdev	No.	Country
Drought	Death	0	0	0		5.02E-04	3.5E-05	4.82E-04	Moldova	1.12E-03	6.2E-05	7.58E-04	Kenya
	Injured	0	0	0		0	0	0		0	0	0	
	Affected	258.55	12.56	137.51	Zambia	1,114.99	40.63	486.00	Tajikistan	1,547.98	42.98	385.60	Malawi
	Homeless	0	0	0		0	0	0		0	0	0	
Earthquake	Death	0.07	3.31E-03	0.04	Japan	0.01	3.5E-04	3.85E-03	Azerbaijan	0.49	0.03	0.47	Pakistan
	Injured	0.34	0.02	0.28	Japan	0.11	5.6E-03	0.07	Azerbaijan	0.89	0.06	0.82	Pakistan
	Affected	10.94	0.33	2.63	Cyprus	5.19	0.16	1.44	China	4.71	0.18	1.69	Chile
	Homeless	3.99	0.16	2.00	Japan	2.93	0.11	1.11	Nicaragua	32.68	2.39	32.10	Pakistan
Flood	Death	0.12	2.74E-03	0.03	Morocco	0.50	2.7E-02	0.36	Bhutan	0.11	3.5E-03	0.05	Guyana
	Injured	0.07	4.36E-03	0.06	China	0.03	8.4E-04	0.01	Thailand	0.02	6.6E-04	0.01	Colombia
	Affected	867.80	21.96	195.55	Azerbaijan	1,195.53	34.27	269.81	Cambodia	562.70	27.95	371.58	Guyana
	Homeless	72.24	2.21	20.30	Azerbaijan	29.59	1.42	18.51	Botswana	13.57	0.50	5.68	Central Africa Rep
Storm	Death	0.11	3.40E-03	0.03	Antigua & Barbuda	0.10	4.3E-03	0.06	Belize	0.25	9.6E-03	0.12	Guatemala
	Injured	2.51	0.18044	2.43	Antigua & Barbuda	2.37	0.17	2.28	Belize	1.35	0.08	1.06	Nicaragua
	Affected	1,144.72	71.23	956.35	Antigua & Barbuda	1,502.62	59.60	627.20	Moldova	282.57	10.36	126.83	Albania
	Homeless	339.63	17.03	213.11	Lao PDR	3.07	0.13	1.57	Philippines	4.94	0.23	2.91	Mexico

Source: EM-DAT (2008)

Notes: Figures greater than 1,000 such as the total number affected by storm in 1995 (≈1,145 affected per 1,000 people) are possible due to instances where there are multiple occurrences of a particular disaster in one country in a given year. "Total no." refers to the sum across the entire sample (196 countries).

Definition:

Death – Persons confirmed as dead and persons missing and presumed dead; Injured – People suffering from physical injuries, trauma or an illness requiring medical treatment as a direct result of a disaster; Homeless – People needing immediate assistance in the form of shelter; Affected people – People requiring immediate assistance during a period of emergency, i.e., requiring basic survival needs, such as food, water, shelter, sanitation and immediate medical assistance. Appearance of a significant number of cases of an infectious disease introduced in a region or a population that is usually free from that disease.

IV. Panel estimation of the losses in capital and income after a natural disaster

The panel data estimation technique is employed to account for the inter-country heterogeneity in the analysis. The expected losses in income as well as capital (natural or human and intangible capital) after a natural disaster are estimated by, first, running regressions with each type of capital as a dependent variable:

$$Capital_{it} = f(X_{jit}, Magnitude\ of\ Natural\ Disaster_{kit}, Lagged\ Magnitude\ of\ Natural\ Disaster_{kit-n}) \qquad (1)$$

For a given country *i* and time period *t*, *Capital* denotes the per capita values of human and intangible capital (HR) or natural capital measured by land resources (L).[3] X_j is a vector of independent variables that influence the dependent variable. Identification of X_j is based on relevant literature, which is described in Appendix 1. *Natural Disaster*$_k$ refers to the *kth* type of natural disaster — i.e., either drought, earthquake, flood or hurricane/storm, while the *magnitude* refers to the number of deaths, injuries, homeless, and affected by a natural disaster. *Lagged Magnitude of Disaster*$_k$ aims to capture any lingering impacts of natural disaster *k* on the dependent variable after it has occurred.

There are two models for panel data estimation: fixed effects and random effects. The *fixed effects* model allows the intercept to differ across the cross-section units by estimating a different intercept for each cross-section, i.e., each country. This is captured by the introduction of dummy variables for the countries (equations 2 and 3). The *random effects* model, on the other hand, assumes that intercepts may be taken as random and hence treated as if they were part of the error term. Also, cross-sectional observations are assumed to be randomly drawn from a sampling distribution; hence, there is no need to include dummy variables to capture the heterogeneity across countries. As a result, the model has an overall intercept, a set of explanatory variables and a composite error term (equations 4 and 5). The composite error term has two parts: a random intercept term and the traditional random error (Kennedy, 2003).

Estimation of the impacts of natural disasters on human and intangible capital and natural capital

The fixed and random effects models for estimating a type of capital are shown below. A logarithmic functional form is used instead of a functional form in levels because it yields more statistically significant results. Other independent variables were initially included in the models and the regression results were compared, particularly the statistical significance of parameter estimates and whether they have the correct signs, and R-squared values. Different measures of impact have also been tried – deaths and injuries, affected and total affected[4] and those that

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[3] Estimations were also done initially for produced/physical capital and energy capital. However, they were later dropped because the measure of physical capital is not affected by the presence of disasters. This does not mean that disasters do not impact on the amount of capital. It does mean that given available data, with only three periods on disasters, one cannot pick up the effects and hence their magnitude is likely to be small compared to other factors that determine differences in the amounts of physical capital between countries. On the other hand, energy capital was found to be very sensitive to natural disasters but the results were not robust and not credible.

[4] *Total Affected* variable is the sum of people who were injured, homeless and affected by a natural disaster.

produce the most robust and credible results have been chosen. The specifications below were selected because they gave relatively robust results and best diagnostic tests, i.e., relatively high R-squared and statistically significant estimates with correct signs:

$$\begin{aligned}\ln HR_{it} &= \alpha + \beta CS_i + \chi \ln RHHFCEPC_{it} + \phi AFFECTED_{it} \text{ by Natural Disaster } k \\ &\quad + \gamma AFFECTED_{it-n} \text{ by Natural Disaster } k + \theta T1995 + \sigma T2000 + \mu_{it}\end{aligned} \tag{2}$$

$$\begin{aligned}\ln L_{it} &= \alpha + \beta CS_i + \ln POPDEN + \ln AGVAPC + CCORRUP + \ln ROADTOT \\ &\quad + \phi AFFECTED_{it} \text{ by Natural Disaster } k + \gamma AFFECTED_{it-n} \text{ by Natural Disaster } k \\ &\quad + \theta T1995 + \sigma T2000 + \mu_{it}\end{aligned} \tag{3}$$

$$\begin{aligned}\ln HR_{it} &= \alpha + \chi \ln RHHFCEPC_{it} + \phi AFFECTED_{it} \text{ by Natural Disaster } k \\ &\quad + \gamma AFFECTED_{it-n} \text{ by Natural Disaster } k + \theta T1995 + \sigma T2000 \mu_{it} + \eta_{it}\end{aligned} \tag{4}$$

$$\begin{aligned}\ln L_{it} &= \alpha + \ln POPDEN + \ln AGVAPC + CCORRUP + \ln ROADTOT \\ &\quad + \phi AFFECTED_{it} \text{ by Natural Disaster } k + \gamma AFFECTED_{it-n} \text{ by Natural Disaster } k \\ &\quad + \theta T1995 + \sigma T2000 + \mu_{it} + \eta_{it}\end{aligned} \tag{5}$$

where *CS* represents a dummy variable for country *i;RHHFCEPC* is real household final consumption expenditure per capita; *POPDEN* refers to population density; AGVAPC is real agriculture value added per capita; CCORRUP, control of corruption index; ROADTOT, total road network; and *AFFECTED* refers to the number of people requiring immediate assistance during a period of emergency, such as food and water.

Alternatively, in place of *AFFECTED*, we also use the impacts of a natural disaster expressed in per capita terms, i.e., affected people per capita (AFFECTEDPC). Different model specifications are presented in the Appendix 2. Natural disaster *k* refers to a type of natural disaster, i.e., drought, earthquake, flood and storm. *T1995* and *T2000* are time dummy variables where 2005 is the base year, η_{it} is the random intercept term and μ_{it} is the traditional error term.

Different *n* lengths of lag (t-1, t-2, t-3, t-n) were included in the model until the coefficient estimate of the last lagged variable (individually or jointly with other time variables) is statistically insignificant. Statistical insignificance implies that the natural disaster has no more impact on the dependent variable.[5] For example, if the coefficient estimate of t-2 is statistically insignificant, it infers that the natural disaster has no more impact on capital by year 2. A joint statistical significance of parameter estimates at *t* and *t-n* imply that the joint or total impacts of a natural disaster on capital are significant during the said periods.

In order to see the impacts of a disaster, we take the aggregate effect of the impacts on the relevant form of capital during different periods (t, t-1, …, t-n). With the regression results from

[5] A study by Gourio (2008) found that GDP bounces back just after the end of a natural disaster. Disaster was measured by the total decline in GDP from peak to trough, where the trough marks the end of the disaster. We assume that capital depicts the same response after a disaster.

the above equations 2 to 5, we will be able to predict the average value of capital with and without the natural disaster. To illustrate using the general model (equation 1),

$$\begin{aligned} With\ disaster = \overline{Capital}_{d,t} &= \hat{a} + \hat{b}\overline{X}_{j,t} + \hat{c}\,\overline{Magnitude\ of\ \ Disaster}_{k,t} \\ &+ \hat{d}\,\overline{Magnitude\ of\ \ Disaster}_{k,t-1} + \hat{e}\,\overline{Magnitude\ of\ \ Disaster}_{k,t-n} \end{aligned} \tag{6}$$

$$Without\ disaster = \overline{Capital}_{0,t} = \hat{a} + \hat{b}\overline{X}_{j,t} \quad \text{since} \quad \overline{Magnitude\ of\ \ Disaster}_{k,t\ \text{and}\ t-n} = 0 \tag{7}$$

where $\overline{X}_{j,t}$ is the average value of a j^{th} independent variable and $\overline{Magnitude\ of\ \ Disaster}_{k,t\ \text{and}\ t-n}$ is the average value of the impacts of a k^{th} type of natural disaster.

Estimation of the impacts of natural disasters on income through impacts of the disasters on capital

We also examine the impacts of natural disasters on the level of output or income, where income is a function of the four types of capital described in section 2. The relationship of output and inputs follows a classical Cobb-Douglas production function:

$$RGDPPC_{it} = AHR_{it}{}^{\beta} PK_{it}{}^{\delta} L_{it}{}^{\phi} E_{it}{}^{\theta} \tag{8}$$

where income is measured by real GDP per capita (RGDPPC), *A* is the efficiency parameter, *HR* is the human capital, *PK* refers to produced or physical capital, *L* denotes land resources and *E* refers to energy resources. In Markandya and Pedroso-Galinato (2007), the efficiency parameter of the nested CES production function is assumed to be a function of the economic indicators (trade openness and private sector investment) and institutional indicators. In this study, *A* is assumed to be a function of *trade openness* (TOPEN) and an *intercept* that accounts for other variables not included.[6] Hence, the production function is specified as follows:

$$RGDPPC_{it} = e^{Intercept+\lambda TOPEN} HR_{it}{}^{\beta} PK_{it}{}^{\delta} L_{it}{}^{\phi} E_{it}{}^{\theta} \tag{9}$$

By taking logs we have, for the fixed effects model:

$$\begin{aligned} \ln(RGDPPC_{it}) &= Intercept + \lambda TOPEN + \beta\ln(HR_{it}) + \delta\ln(PK_{it}) + \phi\ln(L_{it}) + \theta\ln(E_{it}) \\ &+ \gamma CS_i + \mu_{it} \end{aligned} \tag{10}$$

and for the random effects model,

$$\begin{aligned} \ln(RGDPPC_{it}) &= Intercept + \lambda TOPEN + \beta\ln(HR_{it}) + \delta\ln(PK_{it}) + \phi\ln(L_{it}) + \theta\ln(E_{it}) \\ &+ \mu_{it} + \eta_{it} \end{aligned} \tag{11}$$

[6] Private sector investment and institutional indicators (voice and accountability, political stability and absence of violence, government effectiveness, rule of law and control of corruption) were initially included as determinants of *A* but doing so did not yield sensible regression results.

In equation 10, *CS* denotes the dummy variable of country *i*. In equation 11, $(\mu_{it} + \eta_{it})$ is the composite error term of the random effect model. The latter two equations also give us the output elasticity estimates, which measure the responsiveness of income to a change in the levels of human capital, produced capital, land resources or energy resources, *ceteris paribus*. The choice between equation 10 and equation 11 will be based on the Hausman test for random effects.

To estimate the income level *with* the impacts of natural disasters ($RGDPPC_d$), we use the estimated coefficients of equation 10 or 11 and estimated mean values of $\overline{HR}_d$ and $\overline{L}_d$ from equation 6. To simulate the level of income *without* the natural disasters ($RGDPPC_0$), the estimated coefficients of equation 10 or 11 are also used, together with the mean values of $\overline{HR}_0$ and $\overline{L}_0$ from equation 7. Also, the *expected loss of income* (ΔRGDPPC) after the natural disasters can be estimated by obtaining the difference in $RGDPPC_0$ and $RGDPPC_d$.

V. Model specification tests and regression results

Several diagnostic tests were performed on equations 2-5 to determine the appropriate estimation method given available information. First, an F-test was performed on the country dummy variables to verify whether a pooled OLS or panel regression is appropriate. **The F-test rejected the null hypothesis of homogeneity across countries (i.e., all dummy parameters except one = zero). This implies that OLS is not applicable and panel data estimation should be used, either through fixed effects or random effects.** Next, the Hausman specification test was employed to test the null hypothesis of no correlation between the explanatory variables and composite error, i.e., whether the random effects model is appropriate or not. **The Hausman test rejects the null hypothesis, which means that there is correlation and using random effects would yield biased estimators; thus, a fixed effects model is preferred.** Results of the post-estimation tests of different models are summarized in Appendix 2.

Elasticity estimates of impacts of natural disasters on human and intangible capital

We employ the fixed effects model to examine how human capital and natural capital values are affected by the natural disasters, which are measured in terms of the magnitude of impacts.[7] With a semi-log relationship between capital and the impacts of natural disasters, as specified in equations 2-5, the elasticity estimate ($\hat{\varepsilon}$) with respect to the average extent of impacts is given by:

$$\frac{\partial \ln Capital}{\partial Affected_k} = \hat{\phi} * \overline{Affected}_{kt} + \hat{\gamma} * \overline{Affected}_{kt-n} = \hat{\varepsilon} \qquad (12)$$

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[7] Magnitude of disasters has two measures: *Number of People Affected and Number of People Affected Per Capita. "Affected"* refers to people requiring immediate assistance during a period of emergency, i.e., requiring basic survival needs, such as food, water, shelter, sanitation and immediate and medical assistance; and population affected by an infectious disease introduced in their region that is usually free from that disease.

where $\overline{Affected}_{kt}$ and $\overline{Affected}_{kt-n}$ denote the average number of people affected by a *kth* type of natural disaster during period *t* and *t-n*, respectively, across the entire sample. Note that the addition of *t-n* depends on whether or not we find that the joint impacts of the time variables are statistically significant.

Tables 4 and 5 show the elasticity estimates given the *percentage fall* in the value of human and intangible capital per capita (HR) resulting from a one percent increase in the average number of people affected by a specific type of disaster. Two general models have been estimated. In the first model, the elasticity is with respect to the average number of people affected by a disaster (Table 4), while in the second it is with respect to the average number of people affected *per capita* by the disaster, i.e., impacts are normalized for the national population (Table 5). Results from different specifications are presented here because we estimated a number of equations with different combinations of independent variables for sensitivity analyses.

The main points to note about the above results are the following:

- Storms and earthquakes consistently show a significant impact on HR levels. Droughts and floods appear to be significant in the case where the impact is measured by the average number of persons affected but more significant results for both these disasters are found when the impact is measured in per capita terms.

- Given impacts of 2 years duration, the average elasticity of HR with respect to persons affected by storms is 0.018, while that for earthquakes is 0.013. On the other hand, with respect to persons affected per capita, the average elasticities are: 0.006 (earthquakes), 0.006 (storms), and 0.019 (droughts).

- As expected, the reductions in HR are greater when the impacts of a disaster are felt at longer periods. For instance, from Table 5, a percentage increase in the number of people affected per capita by earthquakes with a 2-year duration of impacts leads to a 0.006 percent reduction in HR over the given period. Given impacts of earthquakes for five years, however, there is a 0.09 percent decline in HR for every percentage increase in the number of people affected per capita. This figure is 15 times higher than when the duration of impacts is two years.

Table 4: Elasticity estimates ($\hat{\varepsilon}$) between HR and a disaster type, with respect to the average number of people affected.

Specific-ation	Earthquakes			Storms			Droughts			Floods		
	$\hat{\varepsilon}$		# of Years	$\hat{\varepsilon}$		# of Years	$\hat{\varepsilon}$		# of Years	$\hat{\varepsilon}$		# of Years
1	0.011	**	2	0.012	**	2	--			--		
2	0.014	*	2	0.012	**	2	--			--		
3	0.013	*	2	0.012	**	2	--			--		
4	--			0.026	**	2	0.020	***	1	--		
5	--			0.025	*	2	--			0.466	***	2
Average elasticity given duration of statistically significant impacts												
1 year							0.020					
2 years	0.013			0.018						0.466		

Table 5: Elasticity estimates ($\hat{\varepsilon}$) between HR and a disaster type, with respect to the average number of people affected per capita.

Specific-tion	Earthquakes $\hat{\varepsilon}$		# of Years	Storms $\hat{\varepsilon}$		# of Years	Droughts $\hat{\varepsilon}$		# of Years	Floods $\hat{\varepsilon}$		# of Years
1	0.005	**	2	--			--			--		
2	0.007	**	2	--			--			--		
3	0.004	**	2	--			--			--		
4	0.008	***	2	0.006	*	2	0.019	**	2	0.006	**	1
5	0.038	**	3	0.007	*	1	0.022	**	3	0.005	***	1
6	0.088	**	4	0.020	**	4	0.018	**	4			
7	0.092	***	5	0.031	**	5				0.060	**	5
Average elasticity given duration of statistically significant impacts												
1 year				0.007						0.006		
2 years	0.006			0.006			0.019					
3 years	0.038						0.022					
4 years	0.088			0.020			0.018					
5 years	0.092			0.031						0.060		

Notes for Table 4 and Table 5: Numbers are rounded off to the nearest thousandth. All reported elasticities are significantly different from zero at the one (*), five (**) or ten percent (***) level of confidence. . "# of Years" refers to the duration that the impacts of a disaster are felt. For example, 2 years represent periods *t* and *t-1*. Elasticities corresponding to more than a year of duration mean that the total impacts of periods *t* and *t-n* are statistically significant. "--" means elasticity estimate is statistically insignificant, hence it is not reported. The different model specifications are provided in Appendix 2.

Elasticity estimates of impacts of natural disasters on land resource values

We also estimated the *percentage reduction* in the value of land resources resulting from a one percent increase in the average number of people affected by a natural disaster. Table 6 and Table 7 present the elasticity estimates with respect to the average number of people affected, and as regards the average number of people affected per capita, respectively.

Table 6: Elasticity estimates ($\hat{\varepsilon}$) between land resource values and a disaster type, with respect to the average number of people affected.

Model	Earthquakes $\hat{\varepsilon}$		# of Years	Storms $\hat{\varepsilon}$		# of Years	Droughts $\hat{\varepsilon}$	# of Years	Floods $\hat{\varepsilon}$		# of Years
1	0.110	*	5	0.110	***	5			0.372	***	5
2	0.110	*	5	0.112	***	5			0.377	***	5
3	0.093	*	2	0.067	***	2					
4	0.098	*	2	0.073	**	2					
5	0.093	*	2	0.057	***	2					
Average elasticity given duration of statistically significant impacts											
2 years	0.095			0.066							
5 years	0.110			0.111					0.375		

Table 7: Elasticity estimates ($\hat{\varepsilon}$) between land resource values and a disaster type, with respect to the average number of people affected per capita.

Model	Earthquakes			Storms			Droughts		Floods		
	$\hat{\varepsilon}$		# of Years	$\hat{\varepsilon}$		# of Years	$\hat{\varepsilon}$	Years	$\hat{\varepsilon}$		# of Years
1	0.033	**	2	--			--		--		
2	0.084	***	2	0.015	*	1	--		0.044	***	2
3	0.063	***	2	0.023	*	1	--		0.040	***	2
4	0.040	**	2	0.017	*	1	--		0.064	**	2
Average elasticity given duration of impacts											
1 year				0.019							
2 years	0.055								0.049		

Notes for Table 6 and Table 7: Numbers are rounded off to the nearest thousandth. All reported elasticities are significantly different from zero at the one (*), five (**) or ten percent (***) level of confidence. "# of Years" refer to the duration that the impacts of a disaster is felt. Elasticities corresponding to more than a year of duration mean that there is joint statistical significance in the elasticities of impacts at periods *t* and *t-n*. "--" means elasticity estimate is statistically insignificant, hence it is not reported. The specifications of the different models are provided Appendix 2.

The results show that:

- Earthquakes consistently show a significant impact on the values of land resources, followed by storms then floods. Droughts are not significant.

- When the duration of impacts is two years, the average elasticity of land resource values with respect to persons affected by earthquakes is approximately 0.10, while that for storms is about 0.07. It can also be observed that the average elasticities are higher when the duration of impacts is higher, such as 0.11 for earthquakes and 0.111 for storms if there is a five-year duration of impacts.

- With respect to persons affected per capita, the average elasticity of storms is about 0.02, which is associated with a one-year impact. The average elasticity given a two-year duration of impacts for earthquakes is 0.06 and for floods it is 0.05.

Estimates of losses in human and intangible capital and natural capital following a disaster[8]

The average amount of losses in the values of human and intangible capital or land resources of country *i* due to natural disasters can be estimated using the following equation:

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[8] Gaddis, *et al.* (2007) recommends a full-cost accounting of natural disasters and frames their approach on the coastal disasters in the United States, particularly Hurricane Katrina in the Gulf Coast as a case study. The full cost includes the losses to built, human, natural and social capital due to the natural disaster, and costs of services provided by the four types of capital during disaster relief and recovery. The approach takes into account variables that are not included in typical cost accounting such as: pecuniary effects of natural disaster, indirect effects of disaster at the regional, national or international scale, and effects of the disaster on intangible assets (e.g., non-market goods and services). While this approach can be useful in providing a more complete picture of the various impacts of a natural disaster, the limitation of available data on the national level does not enable us to conduct a micro-level analysis similar to this study. However, the study did not perform an actual full-cost accounting of the hurricane event. Our study, on the other hand, provided an empirical estimation of the losses in capital values.

$$\overline{Losses\ in\ Capital}_i = \frac{\hat{\varepsilon}_k}{100} \times \left(\frac{\overline{Affected}_{i,kt} + \overline{Affected}_{i,kt-n}}{\overline{Affected}_{All,kt} + \overline{Affected}_{All,kt-n}} \right) \times \overline{Capital_i} \qquad (13)$$

where $\overline{Capital}_i$ refers to the average *HR* or *L* of country *i* during the three years —1995, 2000 and 2005; and $\hat{\varepsilon}_k$ is the estimated average elasticity associated with the *kth* disaster (from Tables 4-7).[9] $\overline{Affected}_{i,kt}$ and $\overline{Affected}_{i,kt-n}$ denote the average number of people affected by a *kth* disaster in country *i* at time *t* and *t-n*, respectively. $\overline{Affected}_{All,kt}$ refers to the average number of affected people across the entire sample at time *t*; while $\overline{Affected}_{All,kt-n}$ is similarly defined although it corresponds to time *t-n*. These four latter variables are also expressed in per capita terms for sensitivity analyses.

<u>Human and Intangible Capital (HR)</u>

As an example, we estimate equation 13 using the human and intangible capital (HR) and total impacts of earthquakes events lasting *two years*. Table 8 and Table 9 present the estimated losses in HR of selected countries due to earthquakes, with respect to the number of people affected and people affected per capita, respectively.

Equation (13) shows that the losses in capital are dependent on two factors — the relative magnitude of impacts of a natural disaster (in terms of people affected) and the value of capital. Hence, a relatively higher number of people affected does not necessarily translate to greater losses in the value of human and intangible capital. For instance, in Table 8, the HR losses of Japan (US$246 per capita) are higher compared to that of China ($82 per capita) even though China has a greater number of people affected. Similarly, in Table 9, Japan has higher losses of HR (US$138 per capita) relative to the losses in Turkey (US$34 per capita) and Colombia (US$24 per capita) although Japan has a lower number of affected people per capita.

The upper and lower limits of HR losses can be obtained by calculating the value of losses *plus or minus* the standard error. For example, in Table 8, the HR losses in Mexico ranges between US$19.07 and US$42.11 per capita (i.e., US$30.59 per capita ± US$11.52); while in Table 9, the lower and upper bounds of HR losses are, respectively, US$2.88 and US$10.04 per capita (i.e., US$6.46 per capita ± US$3.58).

[9] We divide this by 100 because the elasticity is expressed as percentage.

Table 8: Estimated losses in human and intangible capital value per capita (HR) due to earthquakes, with respect to number of people affected.

No.	Country	Ave. HR (2005 constant US$)	Affected People in Country *i* (t + t-n)	Average Affected People (t + t-n)	Estimated Elasticity[a]	Losses in HR (2005 constant US$)	
						US$	Std error
1	Australia*	361,092	1,667	20,964	0.013	3.66	1.379
2	Bangladesh****	3,497	333	20,964	0.013	0.01	0.003
3	Chile**	61,922	9,554	20,964	0.013	3.60	1.356
4	China***	5,995	2,256,960	20,964	0.013	82.35	31.005
5	Colombia***	31,351	260,196	20,964	0.013	49.64	18.693
6	India****	3,964	339,866	20,964	0.013	8.20	3.087
7	Indonesia***	6,401	256,522	20,964	0.013	9.99	3.763
8	Japan*	370,999	108,927	20,964	0.013	245.94	92.603
9	Mexico**	78,429	64,078	20,964	0.013	30.59	11.516
10	Pakistan****	5,869	3,588	20,964	0.013	0.13	0.048
11	Turkey**	52,195	354,595	20,964	0.013	112.64	42.411
12	United States*	551,193	8,408	20,964	0.013	28.21	10.620

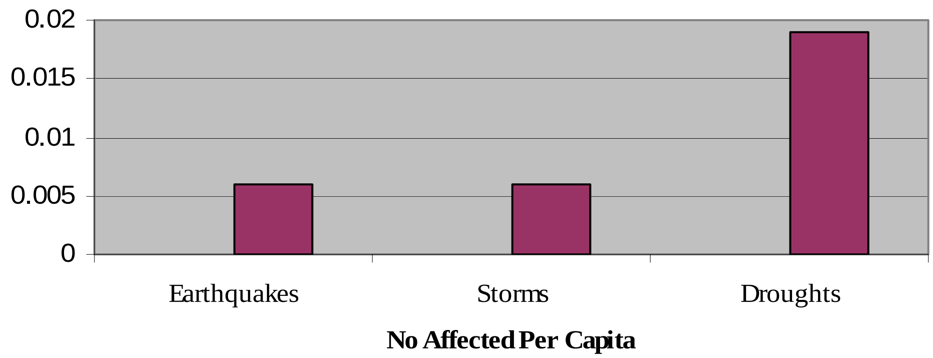
Table 9: Estimated losses in human and intangible capital value per capita (HR) due to earthquakes, with respect to number of people affected per capita.

No.	Country	Ave. HR (2005 constant US$)	Affected People Per Capita in Country *i* (t + t-n)	Average Affected People Per Capita (t + t-n)	Estimated Elasticity[b]	Losses in HR (2005 constant US$)	
						US$	Std error
1	Australia*	361,092	9.33E-05	4.98E-04	0.006	4.12	2.28
2	Bangladesh****	3,497	2.39E-06	4.98E-04	0.006	0.001	0.0006
3	Chile**	61,922	5.90E-04	4.98E-04	0.006	4.46	2.47
4	China***	5,995	1.80E-03	4.98E-04	0.006	1.32	0.73
5	Colombia***	31,351	6.36E-03	4.98E-04	0.006	24.35	13.50
6	India****	3,964	3.24E-04	4.98E-04	0.006	0.16	0.09
7	Indonesia***	6,401	1.26E-03	4.98E-04	0.006	0.99	0.55
8	Japan*	370,999	8.65E-04	4.98E-04	0.006	39.21	21.73
9	Mexico**	78,429	6.75E-04	4.98E-04	0.006	6.46	3.58
10	Pakistan****	5,869	2.36E-05	4.98E-04	0.006	0.02	0.01
11	Turkey**	52,195	5.38E-03	4.98E-04	0.006	34.29	19.01
12	United States*	551,193	2.98E-05	4.98E-04	0.006	2.01	1.11

Notes for Tables 8 and 9: Countries considered are those with non-zero figures for affected people during periods *t* and *t-1*. Also, countries in the table represent four income groups: *,**,***, and **** refer to high income, upper middle income, lower middle income and low income, respectively. *Ave. HR* refers to the average value of HR in country *i* during three years - 1995, 2000 and 2005. "a" and "b" means that the elasticity estimates are from Table 4 and Table 5, respectively.

The results with respect to other disasters will be similar since they will also be a function of the relative elasticity of human and intangible capital, and the relative number of people affected. We can see the impact in terms of *people affected per capita* by simply comparing the relative elasticities. This is done in Figure 1 (we have chosen the per capita specification because in general it performs better in the econometric equations). The figure shows that the impact of an earthquake is the same as that of a storm, while that of a drought is about three times as great[10].

Figure 1:
Elasticity of Human and Intangible Capital w.r.t.
Different Disaters



<u>Land Capital</u>

We also estimate equation 13 using the land capital (L) and total impacts of earthquakes for *two years*. Table 10 gives the estimated losses in L of the same countries listed above, using the number of people affected. Table 11 presents the estimated capital losses, using affected people per capita. In Table 10, the amount of losses in land capital is estimated to be highest in Turkey (US$88 per capita ± US$12), followed by Indonesia (US$63 per capita ± US$8) and Colombia (US$48 per capita ± US$6). In terms of affected people per capita (Table 11), a similar observation can be made — the countries with the most amount of losses in natural capital are Turkey with US$33 per capita ± US$7, Colombia with US$29 per capita ± US$7 and Indonesia with US$8 per capita ± US$2.

[10] The elasticities used in Figure 1 are the ones estimated with a two-year lag. Different lags can give different relative values, although the orders of magnitude are not that different.

Table 10: Losses in land resource values per capita (L) due to earthquakes, with respect to number of people affected.

No.	Country	Ave. L (2005 constant US$)	Affected People in Country *i* (t + t-n)	Average Affected People (t + t-n)	Estimated Elasticity[a]	Losses in L (2005 constant US$)	
						US$	Std error
1	Australia*	13,606	1,667	20,964	0.095	1.02	0.136
2	Bangladesh****	1,696	333	20,964	0.095	0.03	0.003
3	Chile**	2,429	9,554	20,964	0.095	1.05	0.139
4	China***	260	2,256,960	20,964	0.095	26.47	3.519
5	Colombia***	4,104	260,196	20,964	0.095	48.25	6.415
6	India****	2,288	339,866	20,964	0.095	35.13	4.671
7	Indonesia***	5,472	256,522	20,964	0.095	63.41	8.432
8	Japan*	1,653	108,927	20,964	0.095	8.13	1.082
9	Mexico**	7,816	64,078	20,964	0.095	22.63	3.009
10	Pakistan****	3,411	3,588	20,964	0.095	0.55	0.074
11	Turkey**	5,478	354,595	20,964	0.095	87.75	11.668
12	United States*	9,533	8,408	20,964	0.095	3.62	0.482

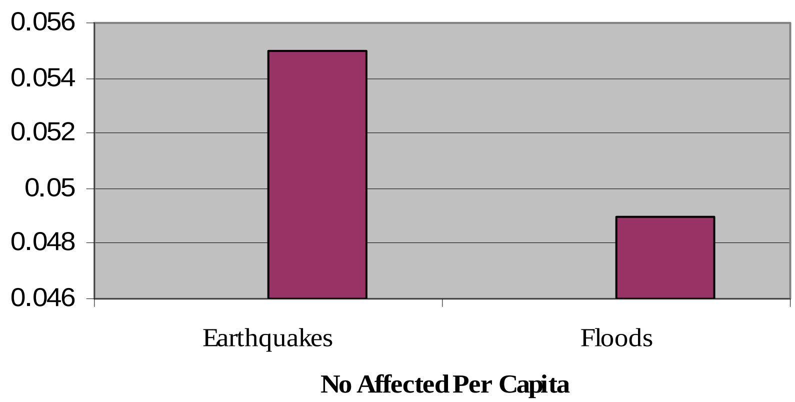
Table 11: Losses in land resource values per capita (L) due to earthquakes, with respect to number of people affected per capita.

No.	Country	Ave. L (2005 constant US$)	Affected People Per Capita in Country *i* (t + t-n)	Average Affected People Per Capita (t + t-n)	Estimated Elasticity[b]	Losses in L (2005 constant US$)	
						US$	Std error
1	Australia*	13,606	9.33E-05	4.98E-04	0.055	1.40	0.319
2	Bangladesh****	1,696	2.39E-06	4.98E-04	0.055	0.00	0.001
3	Chile**	2,429	5.90E-04	4.98E-04	0.055	1.58	0.360
4	China***	260	1.80E-03	4.98E-04	0.055	0.52	0.117
5	Colombia***	4,104	6.36E-03	4.98E-04	0.055	28.87	6.551
6	India****	2,288	3.24E-04	4.98E-04	0.055	0.82	0.186
7	Indonesia***	5,472	1.26E-03	4.98E-04	0.055	7.64	1.730
8	Japan*	1,653	8.65E-04	4.98E-04	0.055	1.58	0.358
9	Mexico**	7,816	6.75E-04	4.98E-04	0.055	5.83	1.326
10	Pakistan****	3,411	2.36E-05	4.98E-04	0.055	0.09	0.020
11	Turkey**	5,478	5.38E-03	4.98E-04	0.055	32.59	7.389
12	United States*	9,533	2.98E-05	4.98E-04	0.055	0.31	0.071

Notes for Tables 10 and 11: *,**,***, and *** refer to high income, upper middle income, lower middle income and low income, respectively. *Ave. L* refers to the average value of L in country *i* during three years - 1995, 2000 and 2005. “a” and “b” mean that the elasticity estimates are obtained from Table 6 and Table 7, respectively.

As in the case of human and intangible capital, the results with respect to other disasters will also be a function of the relative elasticities of land capital, and the relative numbers of people affected. Figure 2 shows a comparison of the elasticities of natural disasters in terms of *people affected per capita*. This is done for the two-year lag specification (again we have chosen the per capita specification because in general it performs better in the econometric equations). The figure shows that the impact of an earthquake is very similar to that of a flood. No impact is expected from a drought, while a storm only has an impact over one year and although not shown in the figure the elasticity is about 40 percent that of the reported ones for earthquakes and floods.

Figure 2: Elasticity of Natural Capital w.r.t Different Disasters



Impacts of natural disasters on income

First, we estimated a Cobb-Douglas production function relating income with four capital inputs (equations 10 and 11). Table 12 provides a comparison of the results from the fixed effects and random effects. The F-test rejects the null hypothesis that all dummy parameters except one are zero, thus implying that a fixed effect model is better than a pooled OLS model. On the other hand, the Hausman specification test rejects the null hypothesis that individual effects are uncorrelated with other regressors in the model (i.e., that random effects is the appropriate method), thereby supporting the use of fixed effects.

Table 12: Fixed and random effects, regression results

Variables	Fixed effects			Random effects		
	Coeff. Estimate	Std error		Coeff. Estimate	Std error	
TOPEN	0.17	0.01	***	3.94E-04	1.13E-03	
ln(HR)	0.40	0.23	***	0.23	0.10	**
ln(PK)	1.17	0.50	**	0.74	0.13	*
ln(L)	0.07	0.04	***	0.13	0.02	
ln(E)	0.10	0.04	**	0.07	0.04	***
Intercept	-9.76	4.17	**	-2.11	0.46	*

Number of observations: 257; F test (99, 152) = 1.94, Prob>F = 0.0001
Hausman test, Ho: individual effects are uncorrelated with other regressors in the model, i.e., random effect model is appropriate. Chi2(5) = 55.97, Prob>chi2 = 0.0000
Notes: *, ** and *** mean statistically significant at 1%, 5% and 10% levels, respectively. TOPEN – trade openness, HR – human capital, PK – produced capital, L – land resources, E – energy resources.

Results of the fixed effect model show that a 10 percent increase in human and intangible capital leads to a 4 percent increase in real GDP per capita, holding other things constant. Also, a 10 percent increase in physical capital, land capital and energy capital results in an increase in real GDP per capita by 12 percent, 0.7 percent and 1 percent, respectively, *ceteris paribus*.

Second, we evaluate the impacts of natural disasters on income by: obtaining the predicted mean values of the two types of capital (human and intangible capital and land capital) *with and without* the impacts of a particular disaster in terms of the average number of people affected per capita[11]; and using these values along with the parameter estimates in Table 12 to estimate equation 10. These impacts are expected to differ in countries due to their strengths of institutions, size of the economy and other characteristics. A comparison of selected countries and groups of countries is therefore presented here. Tables 13 and 14 present the estimated losses in real GDP per capita due to the impact of a particular natural disaster, *ceteris paribus*. In particular, we focus on earthquakes and storms because they consistently show significant impacts on capital across the different models that we estimated, as compared to floods and droughts.

Earthquakes: In Table 13, the expected loss in income due to the impacts of earthquakes, holding other variables constant, is estimated in the range of about US$0.32 to US$1,022 per capita in 1995, US$0.39 to US$127 per capita in 2000 and US$0.31 to US$81 per capita in 2005. The largest losses in income are estimated to be highest in Japan during 1995 and 2005, and in China during 2000. The 1995 and 2005 earthquakes in Japan affected about 205 per 100,000 people and 3 per 100,000 people, respectively; while the earthquake in China during 2000 affected about 144 per 100,000 people.

Table 13. Estimates losses in real GDP (RGDP) per capita with and without the impacts of earthquakes, in 2005 constant US$, selected countries, 1995-2005.

Selected Countries	1995	2000	2005
Average country*	5.95	8.48	12.46
High Income Non-OECD**	16.94	20.62	0.31
High Income OECD**	16.64	19.52	0.40
Low Income**	0.32	0.39	0.51
Low Middle Income**	3.36	4.12	22.25
Upper Middle Income**	6.70	8.17	23.64
Good Governance***	12.03	3.74	1.476
Average Governance***	6.79	15.01	6.32
Poor Governance***	0.35	6.31	1.40
Japan	1,022.23	35.43	80.70
China	55.22	127.43	57.82
Philippines	36.03	0.02	0.00
Australia	12.65	0.00	0.00
Thailand	0.00	0.00	18.01

[11] See Appendix 2. In particular, we use Model 2 in Table A2.2 for human and intangible capital (HR), and Model 3 in Table A2.4 for land capital (L).

Storms. The estimated losses in income caused by storm events are given in Table 14. In general, the impacts of storms result in a general decrease in income between US$0.04 and US$32 per capita in 1995, US$0.03 and US$47 per capita in 2000, and US$0.02 and US$15 per capita in 2005. The highest amount of losses in income due to storm events is estimated for Australia in 1995, for the Philippines in 2000 and for China in 2005.

Table 14. Differences in the value of real GDP (RGDP) per capita with and without the impacts of storm, in 2005 constant US$, selected countries, 1995-2005

Selected Countries	1995	2000	2005
Average country*	2.69	3.72	2.17
High Income Non-OECD**	24.27	29.54	0.02
High Income OECD**	1.44	1.69	0.28
Low Income**	0.91	1.13	0.38
Low Middle Income**	0.73	0.90	4.05
Upper Middle Income**	0.47	0.57	3.34
Good Governance***	0.83	0.67	0.05
Average Governance***	0.74	10.57	1.02
Poor Governance***	0.95	0.03	0.43
Japan	0.01	3.96	14.31
China	2.99	0.67	14.56
Philippines	24.13	46.65	14.66
Australia	175.90	0.70	0.38
Thailand	0.04	0.36	0.10

Notes for Table 13 and Table 14: *Calculated by using the average values of independent variables. **The income groups of countries were based on the World Bank grouping. ***Countries were classified into three levels of governance based on their scores and rankings with respect to the following indicators: Rule of Law, Control of Corruption, Voice and Accountability, Political Stability, Regulatory Quality and Government Effectiveness. "Good Governance" group includes countries whose ranking in the aforementioned indicators falls in the Top 60; "Average Governance" group consists of countries ranked between 61 and 120, and "Poor Governance" group is comprised of countries with ranking of 121 and above. Note that if a country's income loss in a given year is equal to zero, it implies that there is no reported disaster in that country during that year, e.g., Thailand in 1995 and 2000.

VI. Conclusions

This paper presents a set of estimates of the impacts of natural disasters on different forms of capital (physical, human, natural and energy), and thereby on real GDP per capita. The capital database is compiled by the World Bank for three periods – 1995, 2000 and 2005 and for 210 countries. This was combined with data on four types of natural disasters – droughts earthquakes, floods, and hurricanes/storms – for 196 countries, taken from the Emergency Events Database (EM-DAT). The disasters database lists a total of 55 events of drought, 82 events of earthquake, 447 events of flood and 303 events of storm that started during the three years of 1995, 2000 and 2005.

An analysis of the panel data for four forms of capital was carried out using fixed and random effects panel data estimation methods. For each capital, different explanatory variables were used based on the extensive literature on the determinants of these forms of capital. In addition different disasters were included to see how and to what extent they impact on the levels of capital.

At an early stage, we concluded that the measures of physical capital are not affected by the presence of natural disasters. This does not mean that such disasters do not have impacts on the amounts of such capital. It does mean that given available data and with only three years of data on disasters, one cannot pick up such effects and hence their magnitude is likely to be small compared to other factors that determine differences in the amounts of physical capital between countries. On the other hand, energy capital was found to be very sensitive to natural disasters but the results were not robust and not credible. Hence we decided not to include that form of capital in any further analysis.

That left two forms of capital: human and intangible capital (HR) and natural capital (L). The former had to be analyzed as an aggregate of human and intangible taken together because separate estimates of human capital based on education (which is available for some years) was not available for the panel of three years. Since it was felt important to look at the panel so that impacts of disasters could be examined over time, we decided to restrict ourselves to this aggregate, which of course includes social capital and is a complex construct derived as a residual and covering all assets that are not separately identified — i.e., physical and natural capital.

The results of the analysis can be summarized as follows:

1. The values of human and intangible capital are affected by disasters. The measure of disasters is defined in two ways – the numbers affected and the numbers affected per capita. The estimated equations show that storms and earthquakes have a significant impact on HR levels for a wide range of specifications of the underlying model. Variations in the specification include lagged effects of disasters, with the lags varying from one to five years. Droughts and floods appear to be significant in one specification where the impact is measured by the average number of persons affected but more significant results for both these disasters are found when the impact is measured in per capita terms.

2. We quantify these impacts in terms of elasticities, giving the percent reduction in capital as a consequence of a disaster that causes a 1 percent increase in the number of persons affected. When the lags on the disaster variable are limited to two periods the average elasticity of HR with respect to persons affected by storms is 0.018, while that for earthquakes is 0.013. On the other hand, with respect to persons affected per capita, the average elasticities are: 0.006 (earthquakes), 0.006 (storms), and 0.019 (droughts).

3. As expected, the reductions in HR are greater when the impacts of a disaster are felt at longer periods. Unfortunately we are unable to determine the 'right' lag from the estimated equations. The greatest number of significant estimates is obtained with lags of two years, but there are also equations we would consider satisfactory with lags of one to five years. Hence the actual impact of a disaster could be as short as one year or as long as five.

4. The value of land capital is also affected by some disasters. Earthquakes consistently show a significant impact on the values of land resources, followed by storms then floods. Droughts, however, are not found to be significant.

5. When the duration of impacts is two years, the average elasticity of land resource values with respect to persons affected by earthquakes is approximately 0.10, while that for storms is about 0.07. As with HR we observe that the average elasticities are higher when the duration of impacts is higher, such as 0.11 for earthquakes and 0.111 for storms if there is a five-year duration of impacts. With respect to persons affected per capita, the average elasticity of storms is about 0.02, which is associated with a one-year impact. The average elasticity given a two-year duration of impacts for earthquakes is 0.06 and for floods it is 0.05.

6. We used these estimated elasticities to see how much a disaster would reduce the amount of HR and land capital for a 'typical' disaster in selected countries. The loss of capital depends, of course, on the elasticity, but also on the numbers affected in a given country by a typical disaster relative to the number affected across the whole sample of countries. For earthquakes losses of HR per capita from earthquakes ranged from as little as US$0.01 for Bangladesh to as much as US$245.9 for Japan when using the average affected people as the disaster variable; and from as little as US$.001 for Bangladesh to US$39.2 for Japan when using average affected persons per capita as the disaster variable.

7. Similar calculations can be made for other disasters. We do not report detailed figures but we note that they will differ from those for earthquakes in proportion to the elasticities, as well as the relative data on number affected in a typical disaster. Earthquakes and storms have similar elasticities, while droughts have one that is about three times as great.

8. For land capital the losses per capita also range widely: from US$0.03 for Bangladesh to US$87.8 for Turkey when using the average affected people as the disaster variable; and from as little as US$0.0 for Bangladesh to US$32.6 for Turkey when using average affected persons per capita as the disaster variable. In the case of land capital, we would expect a slightly smaller impact in the case of floods. We cannot predict any impact from a drought, while a storm that is about 40 percent that of the reported ones for earthquakes and floods.

9. The losses of land capital and human and intangible capital feed through to losses of income and these, too, have been measured. This supports our assumption that the natural disasters have an indirect impact on income. A Cobb Douglas production function has been estimated using the four capitals and based on that losses from earthquakes are reported in the paper. They amount to US$12.5 per capita in 2005 for an average country, with the highest losses occurring in Japan (US$80.7 per capita) and in China (US$57.8 per capita). A typical low-income country can expect a loss of per capita income of US$0.5 in 2005. For storms the comparable losses of income per capita are: US$2.2 (average country); US$14.3 (Japan); US$14.6 (China); US$14.7 (Philippines); and US$0.4 (typical low-income country).

10. As noted earlier, these estimates are national level figures and cannot be useful in predicting losses at the local level, where much bigger amounts can be experienced per capita. Nevertheless, they do provide some indication of magnitudes for different disasters and for different groups of countries. More work and more data are needed to get a dynamic profile for the losses of capital and income; the best we can say is that the time profile is typically between 2 and five years.

11. Broadly, quantitative analysis shows that the impacts of natural disasters on a nation's income or output come through their indirect effects on capital, i.e., human and intangible capital and natural capital. This has some important policy implications, one of which is that, when considering which recovery measures to implement, attention needs to be paid to re-building these forms of capital.

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Appendix 1
Determinants of capital

I. Human capital is based on Barro and Lee (2000), which measured educational attainment as a reasonable proxy for the stock of human capital. Educational attainment is a function of the overall years of schooling and composition of attainment at various levels of education. For a particular determinant, data for more than one variable may be collected so that we can choose which has a better quality of data (e.g., more complete data, more variation in the data across the sample).

Table A1.1. Determinants of Human Capital.

Determinants	Description	References	Notes	Data source
Household income	Represents the resources available to support the children's education.	Holmes (1999); Malik et al. (2005); Phoumin (2008); Bacolod and Ranjan (2008); Dancer and Rammohan (2007); Deolalikar (1997); Ray (2001); McGavin (1981)	It is difficult to gather this data at the country level. Data will be gathered for "household final consumption expenditure (current US$)" as an alternative.	World Bank-World Development Indicators (WDI) database
Wages (10-45 years old)	Wages affect schooling outcomes but the direction of influence is uncertain. Higher wages infer that resources are available to finance education; however, it can also be examined in terms of opportunity cost. Higher wage rates may lead parents to spend more time in the labor market, which reduces their time to attend to their children's learning at home. This will then affect the children's attainment of education. Furthermore, higher wages paid to young workers may lead to children dropping out of school and enter the labor market, which would also depress school attainment.		The WDI do not have data on this particular variable. As an alternative, data will be gathered on variables that capture labor market conditions: o Child employment in: agriculture, manufacturing, and services (% of children ages 7-14) o Total unemployment (% of total labor force)	WDI

Table A1.1. Determinants of Human Capital (continued).

Determinants	Description	References	Notes	Data source
Public expenditure on education	Investments on education captures the priority given by national governments on education. This expenditure gives resources to promote and support literacy and school attainment of the population.		Data for the following will be gathered: o Public spending on education, total (% of GDP) o Public spending on education, total (% of government expenditure)	WDI
Community infrastructure	The presence of infrastructure (e.g., sewage disposal) may indicate hygiene practices in the area which affect a person's health, which is a complement to learning and school attendance.		Data for the following will be gathered: o Improved sanitation facilities (% of population with access) o Improved water source (% of population with access) o Health expenditure, total (% of GDP)	WDI
Poverty status	This variable will complement the variables on income. Very low income has implications for schooling especially concerning the provision of necessary textbooks for school youth, payment of prescribed school fees and the provision of other necessities like nutrition.		Data needed: o Poverty headcount ratio at national poverty line (% of population) o GINI index	WDI
Other community characteristics	These variables will capture the different characteristics of the countries considered in the study.		Data needed: o Pupil-teacher ratio, primary – has influence on children's learning; o Vehicles per 1,000 people; Vehicles per km of road; Roads, paved (% of total roads) – represent accessibility to the school and others	WDI

There are other variables that influence human capital (schooling) that were identified in the literature: household size, parent's educational attainment and travel time to school. However, data are difficult to obtain and we can assume that their characteristics are somehow captured by the variables listed in the table above.

II. Land resources are the aggregated value of cropland, pastureland and protected areas. The important determinants of land use are listed below.

Table A1.2. Determinants of Land Resources.

Determinants	Description	References	Notes	Data Source
Income from agriculture	This variable captures the importance of agriculture to the economy.	Turner, et al. (1993); Lopez and Galinato (2005a,b); Irwin (2006)	Agriculture, value added (% of GDP)	WDI
Demographic factors	Major determinants of land use include demographic factors such as population size and density.		Data needed: o Total population o Population density (people per sq. km.)	WDI
Access to roads	A priori, the impact of this variable on land resources is unclear. It measures the accessibility of transport of inputs and outputs that support agriculture; hence a positive relationship between roads and cropland. On the other hand, this variable can also capture higher degree of accessibility to pastureland and protected areas, which may contribute to resource degradation.		Data will be obtained for: o Roads, paved (% of total roads) o Roads, total network (km)	WDI
Economic development	High level of income signals available resources for environmental protection		Data will be obtained for: o GDP per capita (current US$)	WDI

Note: Lopez and Galinato (2005a, 2005b) focus on the causes of deforestation, but they also discuss agriculture. Furthermore, the variables that they used, such as access to roads, are also relevant for land resources considered in our study.

Table A1.2. Determinants of Land Resources (continued).

Determinants	Description	References	Notes	Data Source
Political structures, public services and policies	Institutions have an impact on how resources are allocated and used.		We already have data for the following indicators of governance: o Government effectiveness - perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. o Rule of Law –perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. o Control of corruption - perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests.	World Bank, Governance Indicators
			Polity data – political regime or patterns of authority. Countries with larger positive (negative) polity values have a more democratic (autocratic) system. The democracy variable aims to measure the degree of civil society participation, government transparency, and quality of institutions.	Integrated Network for Societal Conflict Research (INSCR) Data Page

Appendix 2
Model specifications

Table A2.1. Model specification using *number of people affected* by natural disasters, dependent variable: ln(Human and Intangible Capital value per capita).

Model	Independent variables	N	R-square	F-test P-value*	Hausman test Chi^2 P-value**
1	ln(Improved water sources) AFFECTED by Natural disaster *k* at t AFFECTED by Natural disaster *k* at t-1 Dummy for time variables = T1995, T2000	328	0.981	0.000	0.000
2	ln(Real household final expenditures per capita) AFFECTED by Natural disaster *k* at t AFFECTED by Natural disaster *k* at t-1 Dummy for time variables = T1995, T2000	365	0.978	0.000	0.000
3	ln(Improved water sources) ln(Real household final expenditures per capita) AFFECTED by Natural disaster *k* at t AFFECTED by Natural disaster *k* at t-1 Dummy for time variables = T1995, T2000	323	0.980	0.000	0.000
4	ln(Real household final expenditures per capita) ln(Pupil-teacher ratio in primary education) AFFECTED by Natural disaster *k* at t AFFECTED by Natural disaster *k* at t-1 Dummy for time variables = T1995, T2000	213	0.992	0.000	0.000
5	ln(Real household final expenditures per capita) ln(Pupil-teacher ratio in primary education) ln(Unemployment rate) AFFECTED by Natural disaster *k* at t AFFECTED by Natural disaster *k* at t-1 Dummy for time variables = T1995, T2000	123	0.993	0.000	0.001

Notes: N means number of observations. R-square is for fixed effects model.
*Reject null hypothesis of homogeneity across countries at 1 percent level.
**Reject null hypothesis of no correlation between explanatory variables and composite error, i.e., random effects model is appropriate, at 1 percent level.

Table A2.2. Model specification using *number of people affected per capita* (AFFECTEDPC) by natural disasters, dependent variable: ln(Human and Intangible Capital value per capita)

Model	Independent variables	N	R-square	F-test P-value*	Hausman test Chi^2 P-value**
1	ln(Improved water sources) AFFECTEDPC by Natural disaster *k* at t AFFECTEDPC by Natural disaster *k* at t-1 Dummy for time variables = T1995, T2000	328	0.9809	0.000	0.000
2	ln(Real household final expenditures per capita) AFFECTEDPC by Natural disaster *k* at t AFFECTEDPC capita by Natural disaster *k* at t-1 Dummy for time variables = T1995, T2000	364	0.9784	0.000	0.000
3	ln(Improved water sources) ln(Real household final expenditures per capita) AFFECTEDPC by Natural disaster *k* at t AFFECTEDPC by Natural disaster *k* at t-1 Dummy for time variables = T1995, T2000	323	0.9805	0.000	0.000
4	ln(Real household final expenditures per capita) ln(Pupil-teacher ratio in primary education) AFFECTEDPC by Natural disaster *k* at t AFFECTEDPC by Natural disaster *k* at t-1 Dummy for time variables = T1995, T2000	213	0.9925	0.000	0.001
5	ln(Real household final expenditures per capita) ln(Pupil-teacher ratio in primary education) AFFECTEDPC by Natural disaster *k* at t AFFECTEDPC by Natural disaster *k* at t-1 AFFECTEDPC by Natural disaster *k* at t-2 Dummy for time variables = T1995, T2000	213	0.9928	0.000	0.009
6	ln(Real household final expenditures per capita) ln(Pupil-teacher ratio in primary education) AFFECTEDPC by Natural disaster *k* at t AFFECTEDPC by Natural disaster *k* at t-1 AFFECTEDPC by Natural disaster *k* at t-2 AFFECTEDPC by Natural disaster *k* at t-3 Dummy for time variables = T1995, T2000	213	0.9931	0.000	0.009
7	ln(Real household final expenditures per capita) ln(Pupil-teacher ratio in primary education) AFFECTEDPC by Natural disaster *k* at t AFFECTEDPC by Natural disaster *k* at t-1 AFFECTEDPC by Natural disaster *k* at t-2 AFFECTEDPC by Natural disaster *k* at t-3 AFFECTEDPC by Natural disaster *k* at t-4 Dummy for time variables = T1995, T2000	213	0.9934	0.000	0.019

Notes: N means number of observations. R-square is for fixed effects model.*Reject null hypothesis of homogeneity across countries at 1 percent level. **Reject null hypothesis of no correlation between explanatory variables and composite error, i.e., random effects model is appropriate.

Table A2.3. Model specification using *number of people affected* by natural disasters, dependent variable: ln(Land Capital value per capita).

Model	Independent variables	N	R-square	F-test P-value*	Hausman test Chi^2 P-value**
1	ln(Population density) AFFECTED by Natural disaster *k* at t AFFECTED by Natural disaster *k* at t-1 AFFECTED by Natural disaster *k* at t-2 AFFECTED by Natural disaster *k* at t-3 AFFECTED by Natural disaster *k* at t-4 Dummy for time variables = T1995, T2000	541	0.746	0.000	0.080
2	ln(Population density) Rule of Law AFFECTED by Natural disaster *k* at t AFFECTED by Natural disaster *k* at t-1 AFFECTED by Natural disaster *k* at t-2 AFFECTED by Natural disaster *k* at t-3 AFFECTED by Natural disaster *k* at t-4 Dummy for time variables = T1995, T2000	524	0.744	0.000	0.023
3	ln(Population density) ln(Real Agriculture Value Added per capita) Rule of law Control of corruption Polity ln(Road total network) AFFECTED by Natural disaster *k* at t AFFECTED by Natural disaster *k* at t-1 Dummy for time variables = T1995, T2000	202	0.871	0.000	0.085
4	ln(Population density) ln(Real Agriculture Value Added per capita) Government effectiveness Rule of law Control of corruption Polity ln(Road total network) AFFECTED by Natural disaster *k* at t AFFECTED by Natural disaster *k* at t-1 Dummy for time variables = T1995, T2000	202	0.874	0.000	0.090
5	ln(Population density) ln(Real Agriculture Value Added per capita) Polity ln(Road total network) AFFECTED by Natural disaster *k* at t AFFECTED by Natural disaster *k* at t-1 Dummy for time variables = T1995, T2000	214	0.840	0.000	0.050

Notes: N means number of observations. R-square is for fixed effects model.
*Reject null hypothesis of homogeneity across countries at 1 percent level.
**Reject null hypothesis of no correlation between explanatory variables and composite error, i.e., random effects model is appropriate.

Table A2.4. Model specification using *number of people affected* by natural disasters, dependent variable: ln(Land Capital value per capita).

Model	Independent variables	N	R-square	F-test P-value*	Hausman test Chi^2 P-value**
1	ln(Population density) ln(Real Agriculture Value Added per capita) AFFECTEDPC by Natural disaster *k* at t Dummy for time variables = T1995, T2000	482	0.686	0.000	0.0144
2	ln(Population density) ln(Real Agriculture Value Added per capita) Polity AFFECTEDPC by Natural disaster *k* at t Dummy for time variables = T1995, T2000	334	0.761	0.000	0.012
3	ln(Population density) ln(Real Agriculture Value Added per capita) Control of corruption ln(Road total network) AFFECTEDPC by Natural disaster *k* at t AFFECTEDPC by Natural disaster *k* at t-1 Dummy for time variables = T1995, T2000	290	0.802	0.000	0.017
4	ln(Population density) ln(Real Agriculture Value Added per capita) Control of corruption AFFECTEDPC by Natural disaster *k* at t AFFECTEDPC by Natural disaster *k* at t-1 Dummy for time variables = T1995, T2000	452	0.690	0.000	0.002

Notes: N means number of observations. R-square is for fixed effects model.
*Reject null hypothesis of homogeneity across countries at 1 percent level.
**Reject null hypothesis of no correlation between explanatory variables and composite error, i.e., random effects model is appropriate.